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Review

Building Thermal-Network Models: A Comparative Analysis, Recommendations, and Perspectives

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Abstract: The development of smart buildings, as well as the great need for energy demand reduction, has renewed interest in building energy demand prediction. Intelligent controllers are a solution for optimizing building energy consumption while maintaining indoor comfort. The controller efficiency on the other hand, is mainly determined by the prediction of thermal behavior from building models. Due to the development complexity of the models, these intelligent controllers are not yet implemented on an industrial scale. There are primarily three types of building models studied in the literature: white-box, black-box, and gray-box. The gray-box models are found to be robust, efficient, of low cost computationally, and of moderate modeling complexity. Furthermore, there is no standard model configuration, development method, or operation conditions. These parameters have a significant influence on the model performance accuracy. This motivates the need for this review paper, in which we examined various gray-box models, their configurations, parametric identification techniques, and influential parameters.

Keywords: building energy; building energy management system (BEMS); gray-box models; lumped-parameter models; smart building; system identification; thermal-network models



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1. Introduction

The need for the development of a sustainable environment is of the utmost importance to reduce the effects of climate change and global temperature increase due to the significant rise in the emissions of greenhouse gases (GHGs) such as CO₂, CH₄, N₂O, HFC, PFC and SF₆. According to the International Energy Agency (IEA) [1,2], the buildings and construction sector is responsible for almost 35% of global primary energy consumption, which is much higher than the other sectors, i.e., transport (28%), and industries (32%). Similarly, the buildings and construction sector accounts for 38% of CO₂ emissions (Figure 1). Whereas, in European Union (EU) buildings account for almost 40% of energy consumption and 36% of CO₂ emissions. The increase in emissions from the buildings sector is attributable to the continued use of coal, oil, and natural gas for heating and cooking, combined with rising activity levels in locations where electricity remains carbon-intensive, resulting in stable direct emissions but increasing indirect emissions, i.e., electricity [3]. Without timely action, building-related GHG emissions are anticipated to double or possibly triple by 2050 [4].

Many industrialized countries have made significant efforts in this regard, with stringent rules, ambitious goals, and incentives for renewable energy integration [5,6]. International communities and organizations have been hyperactive in drafting new global policies to tackle the climate change problem. A road-map for the global energy sector has been developed by IEA to achieve net-zero by 2050 [7], which stipulates a 75% increase in overall floor area between 2020 and 2050. Consequently, the demand for heating, ventilation, and air-conditioning systems (HVAC) will grow significantly, despite this demand

growth, total CO₂ emissions from the buildings sector decline by more than 95% from almost 3 Gt in 2020 to around 120 Mt in 2050 in the net-zero energy scenario (NZE) [7]. Energy efficiency and electrification are the two main drivers of the decarbonization of the buildings sector in NZE. Although the integration of renewable energy into buildings leads to a reduction in energy dependency, it cannot be considered for a complete reduction in energy consumption and emissions. This transformation is based mostly on commercially/industrially accessible technologies, including improved envelopes for new and existing buildings [8], e.g., phase-change materials [9], highly insulating materials [10], heat pumps [11], energy-efficient appliances [12], occupancy behavior analysis [13], and intelligent building controllers [14].

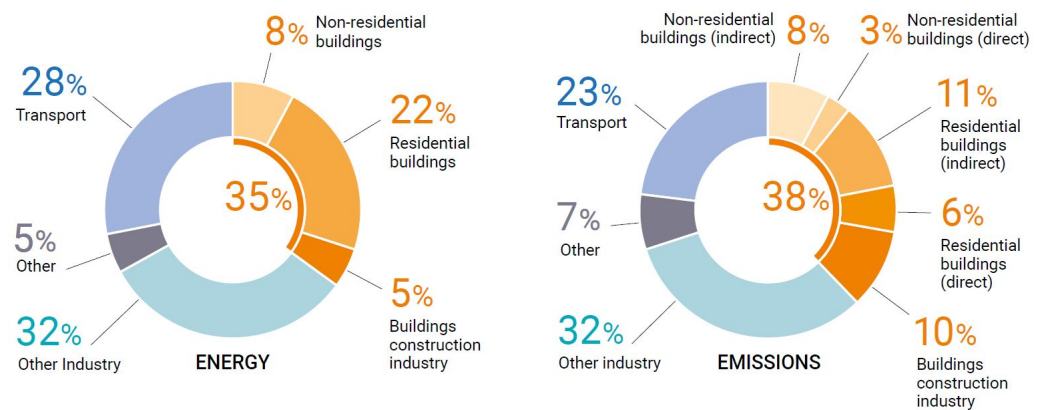


Figure 1. Global share of final energy and emissions by sector, 2019 [1–3].

A zero-carbon building is extremely energy efficient and uses either renewable energy directly, or an energy source that will be entirely decarbonized by 2050, such as electricity or district heat. This means that a zero-carbon-ready building will become a zero-carbon building by 2050 without any further changes to the building or its equipment [7]. The road-map to mitigate global direct CO₂ is represented in Figure 2, and the global energy consumption from fuel and end-use applications in Figure 3. Collectively, occupancy behavior and energy efficiency constitute between 40–50% of the total activities required to achieve the 2030 objective. This means more efficient energy appliances, energy-aware occupants, and intelligent building control systems are necessary for this process. As a result, building operation and management practices have a major impact on the reduction of energy consumption and peak demand response.

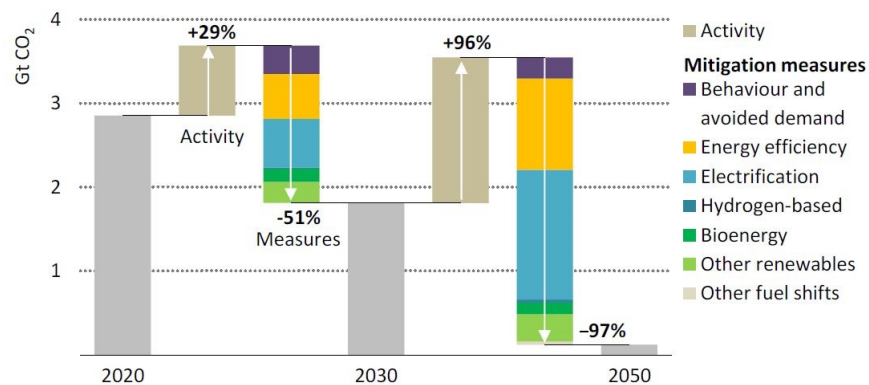


Figure 2. Global direct CO₂ emission reductions by mitigation measure in buildings in the NZE [7].

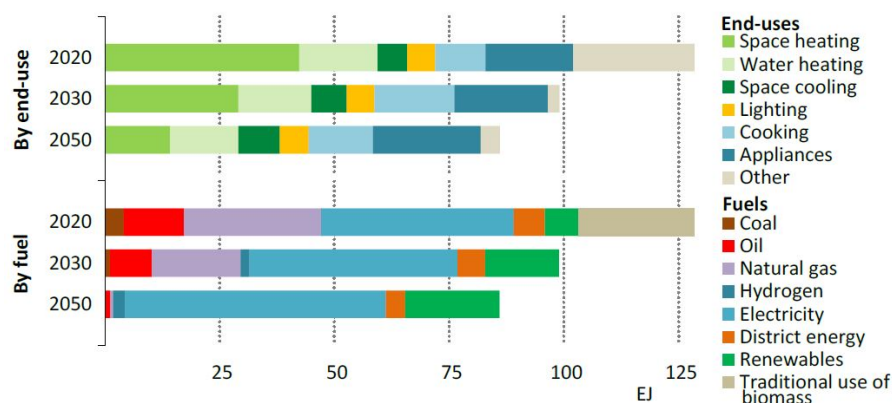


Figure 3. Global final energy consumption from fuel and end-use applications in buildings in the NZE [7].

A building energy management system (BEMS) is a sophisticated computerized system for monitoring and controlling a building's energy needs [15–17]. It is connected to HVAC systems and electrical appliances through sensors, and communication networks [18]. Building energy management systems provide real-time monitoring and control for a range of integrated systems that are used to maintain the indoor comfort levels set by occupants/users [19,20]. However, these systems have already been in use for the last two decades yet energy management has not been significantly improved due to the poor controller strategies/methodologies that have been implemented. Conventional ON/OFF controllers, single objective controllers, rule-based controllers, etc., are mainly used for temperature control [14]. In the last decade, there has been a surge in the amount of research focused on multi-objective controllers. The application of data-driven controllers [21,22], and model predictive controllers (MPCs) [23–26] has shown significant accuracy in controlling the multiple objectives. However, buildings are heterogeneous systems (complex networks of appliances and sensors) and the necessity of multi-objective applications for controllers made their design and development extremely challenging and time-consuming. Furthermore, these real-time controllers are model-based controllers and their performance accuracy is greatly dependent on the building model accuracy. Low-order models that can replicate the thermal dynamics of a building with high accuracy and low computational cost are useful for model-based controllers [27]. However, due to all these reasons the industrial application of such multi-objective controllers is still difficult and expensive.

Building Thermal Models

There are several approaches and models for energy performance analysis in buildings (Figure 4). No single approach is universally suitable for all buildings. Rather, the choice of which model is best for any given application depends on what you choose to quantify and what data is available. These various models can be broadly categorized into two types:

- Steady-state models
- Dynamic/Transient models

Steady-state approaches appeal to applications where simplicity is key, and their lack of data prevents more detailed and precise transient analyses. Steady-state analysis simplifies the necessary calculations by neglecting thermal capacitance, dynamic temperature changes, occupants' influence on the system, and heat sources. Steady-state modeling is useful when there is not much data available and for long-duration energy analysis [28].

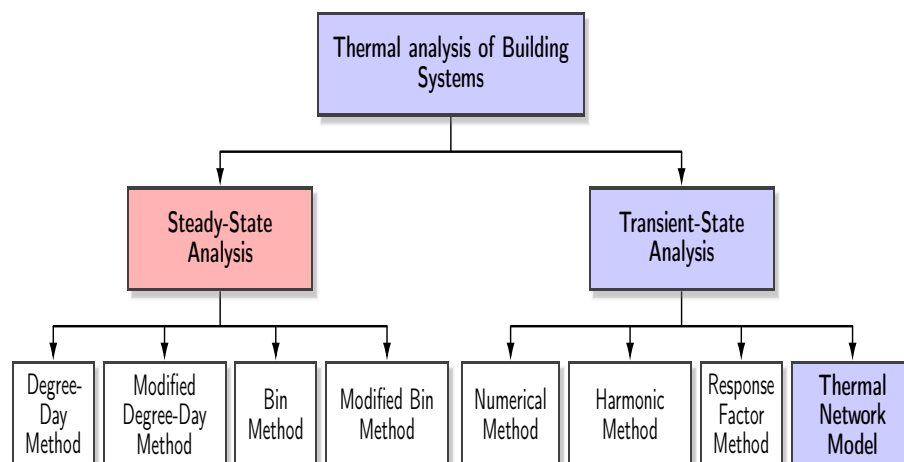


Figure 4. Building thermal modeling approaches.

However, real-time controllers are based on transient models. Researchers have developed and suggested various dynamic models for buildings. These can be divided into three categories:

- Analytical (white-box) models: are a physical modeling approach relying on thermodynamic and/or mathematical equations, and engineering methods for energy modeling. Some examples are the building energy analysis simulation software programs such as EnergyPlus [29], the Transient System Simulation Tool (TRNSYS) [30], eQuest, etc. Data for all the thermo-physical characteristics are required to develop white-box models. The complexity of these models increases with an increase in the size of a building, thus resulting in high computational costs. These models are not suitable for controller applications.
- Data-driven (black-box) models: are data-driven building energy models, which are built on the basis of available data [31,32] are often considered easy to model compared to physics-based white-box models. Black-box model examples are Artificial Neural Networks (ANNs) [33], Support Vector Machines (SVM) [34], Genetic Algorithms (GAs) [35], Reinforcement Learning models (RL), deep machine learning models [36], etc. Aside from their ease of application, black-box models, require large amounts of input data to train the model. This data may not be available in buildings where sensors are not installed, thereby limiting their application to the few buildings with installed sensors.
- Hybrid (gray-box) models: to overcome white-box and black-box model drawbacks, hybrid (gray-box) models were introduced [37]. Gray-box models are a combination of physics-based models (white-box models) and statistical methods (black-box models). Gray-box modeling is found to be the most robust and accurate method for modeling building systems and improving building performance [38]. These models were mainly developed using the lumped-capacitance method, which includes a network of thermal resistors and capacitors (called a thermal-network model).

In the literature, many review papers have been published on energy efficient buildings in the contexts of both construction and operation. These mainly focused on sustainable building design [39], BEMS [40], Building Information Modeling (BIM) [41,42], building material [43], policies [6], retrofitting buildings [44], building energy modeling [14,45], lighting systems [46], and building control techniques [47–49]. Several papers reviewed controller techniques, i.e., data-driven models [21,50], fuzzy logic [51], cyber-physical systems [52] and MPCs [53,54]. The papers also reviewed comfort management [55], and occupancy behavior and prediction [13,56]. The summary and main topics of the above reviews are summarized in Table 1.

Table 1. State-of-the-art reviews related to building modeling and building energy management systems.

Topic	Reference	Details
BEMS	[40]	A comprehensive study of the research related to computational optimization applied for sustainable building development. The study covers a range of topics from building envelopes to the energy systems installed in buildings.
BEMS	[40]	Energy management systems and strategies in the context of buildings are reviewed. Particularly focused on the different energy management systems (EMS) implemented in buildings.
Building energy modeling	[45]	Studies of building energy management systems and strategies in relation to human dimensions are reviewed.
BEMS	[14]	The authors conducted a comprehensive review of recent intelligent building controllers. This review also discusses three building modeling categories and compare them based on their application and robustness.
Building envelope materials	[43]	A comprehensive review carried out regarding the use of different building materials. The paper mainly focuses on phase-change materials (PCMs), with more than 150 different PCMs being reviewed.
Data-driven models	[50]	The authors conducted a detailed review of the models that are developed based on available data.

Despite the considerable amount of review papers that have been published on building energy modeling, comfort management, occupancy behavior and prediction, controlling techniques, and HVAC systems. There is still a lack of reviews concerning simplified models that mainly focused on thermal-network models. Kramer et al. [57] reviewed simplified thermal models for buildings and addressed many questions such as: *What kind of modeling approaches are applied?*, *What are their (dis)advantages?*, and *What are important modeling aspects?*. Similarly, Bagheri et al. [58] reviewed thermal network methods for buildings, and compared them to the other tools, e.g., software tools. Unlike these review papers, this paper presents a comprehensive and critical analysis of building thermal-network models. Furthermore, we have reviewed thermal-network modeling methods, categorized them as: direct, inverse, and hybrid models. Different configurations and influential parameters are also highlighted and critically discussed. We have compared different parametric identification techniques and their computational costs. Finally, we have provided a discussion on the topics of model selection, future perspectives, and recommendations.

The papers that are reviewed in this study are selected by following a thorough filtering process. Initially, an elementary search was conducted by using search engines: Google Scholar, Scopus, Science Direct, and IEE Xplore digital library. For the review process, the keywords ‘thermal-network model’, ‘Lumped Capacitor’, ‘lumped thermal’, ‘Gray-box models’, ‘Lumped-parameter models’, and ‘Building energy management systems’ were used to filter papers. Furthermore, only papers from top international journals and indexed conference proceedings were considered, resulting in 120–130 papers being considered for this state-of-the-art review based on these selection criteria.

2. Thermal-Network Models

The analogy between thermal and electrical systems [59] (Table 2) is frequently used to develop simple and efficient models for the thermal analysis of buildings. In these simplified models, the distributed thermal conductance and capacitance are typically lumped together to avoid the use of complex partial differential equations for heat conduction. Furthermore, radiative and convective heat transfers can also be included in the thermal-network model by using appropriate thermal resistance values [60]. The number of capacitors present in the network determines the order of the ordinary differential equation. The resulting equivalent mathematical equations can be represented using state-space equations for computationally efficient simulations [61].

Table 2. Thermal to Electrical System analogy.

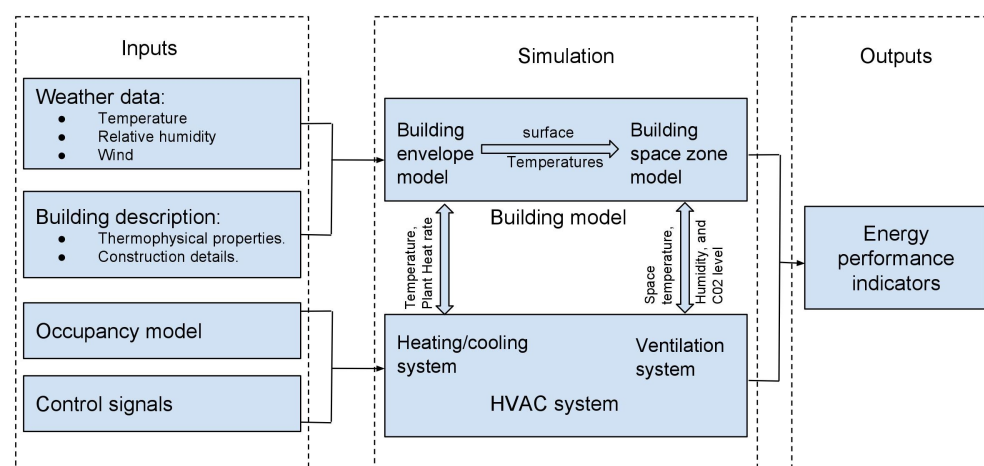
	Thermal System	Electrical System
Source	Temperature (T) Heat flux (ϕ)	Voltage (V) Current (I)
Element	Thermal conductivity (k) Thermal resistance (R) Thermal capacity (C)	Conductivity (σ) Electrical resistance (R) Electrical capacitance (C)

The basic concept of these models is that temperature only varies with time and remains constant across the walls and windows regardless of other changes. The Biot number (Bi) is used in heat transport calculations [62]. These models help to obtain simplified/reduced building models with higher efficiencies.

In the literature, many thermal network configurations have been proposed. The type of building, the number of zones, the type of activities, the materials used, and the application all have a role in these differences. Models of the building envelope, such as walls, windows, and internal mass, are used to develop the equivalent thermal-network circuit of a zone. The building is divided into a network of nodes with interconnecting paths through which energy flows in a thermal-network model [63,64]. The method's applicability varies substantially depending on the nodes where energy balancing is performed. There are mainly three types of models that can be developed:

1. Model for a building envelope (walls, floors, roofs, etc.).
2. Model for space-zone and its thermal interactions with the envelope.
3. Model for a complete zone.

Whilst, there is no huge difference between these methods, the model for a complete zone is developed by aggregating the individual envelope models into a single model, and integrating this with the space-zone model (see Figure 5). Whereas, the specific model for the building envelope is significant in knowing surface temperatures, in the analysis of individual envelope dynamics, etc.

**Figure 5.** Development of a thermal-network model for a building zone [65].

2.1. Building Envelope Models

The part of the building structure that is exposed to the environment is called the building envelope. Furthermore, the majority of a building's overall heat transmission occurs through the building envelope. As a result, to effectively replicate real heat dynamics at a low computational cost, an efficient thermal-network model is required. The configurations of these models, on the other hand, are not explicit and are dependent on the number of layers and the thermo-physical properties of the materials. Conduction,

convection, and radiation heat transfer are represented by the capacitors and resistors in the model.

Several configurations have been proposed in the literature to describe the thermal dynamics of the building envelope. These combinations are chosen based on the wall’s composition, attributes, simulation time stamp, Biot number, and application. Figure 6 depicts an overview of several configurations proposed in the literature. Lorenz and Massy [66] presented an early implementation of a thermal network for building envelopes, introducing a 2R1C configuration for external walls and a 1R1C configuration for internal walls. The accessibility factor was used to calculate the position of capacitance in the 2R1C model. This simple approach has a number of significant benefits: the thermal response analysis may be performed on low-cost, widely available computers (PCs) and still get substantially accurate results with minimal amounts of effort and time. Furthermore, the basic thermal network provides an easy-to-understand physical meaning for researchers and designers.

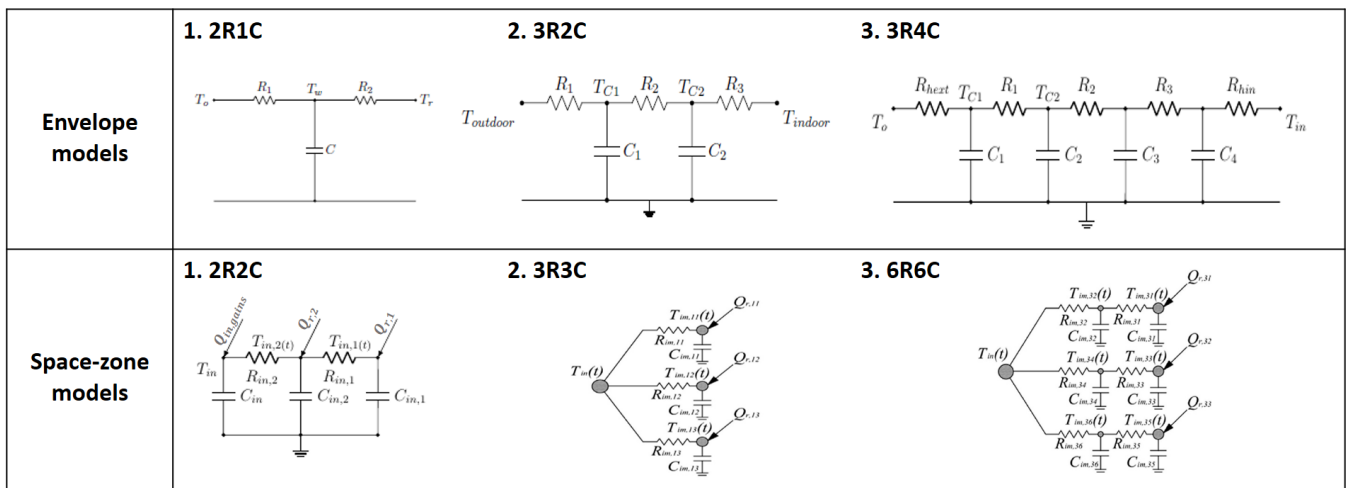


Figure 6. Major configurations of envelope and space-zone models. Reproduced from Boodi et al. [27], Fraisse et al. [67], Wang & Xu [68], and Ji et al. [69].

Similarly, Hassid [70] proposed the 2R1C model for external walls and adapted it to passive solar structures. He found that this method can be used to estimate the heating requirements of passive solar dwellings as a first-order adjustment to the degree-day method. When applied to medium or moderate thermal capacity structures, however, the second-order model (one capacitor for the envelope and another for the inside air mass) resulted in over-responsiveness. Tindale developed a third-order model to address this problem in his study [71]. He also demonstrated an analytical method for determining its parameters. When utilized on a light thermal mass, the model showed considerable advantages over the second-order model without sacrificing computing performance. Despite an increase in accuracy over the previous model, the second-order model’s performance in heavy thermal mass structures is still low. Lombard and Mathews [72] also used the RC model to simulate building heat transfer in a 2-port envelope model (second-order model). The space zone was represented by a single heat-storage capacitance. The model was applied on a one-story commercial building, and the overall sensible cooling load and instantaneous sensible heat gain results were compared to the commercial building example in ASHRAE Fundamentals [15].

These approaches and thermal structures were also implemented by Gouda et al. [73] for the ceiling, floor, and interior walls. The more sophisticated model, which includes a 2R1C thermal network for each construction element (external walls, internal partition, floor, and ceiling construction), outperformed the simpler model in terms of performance and computing efficiency. This improvement in the model, which involves simulating thermal dynamics using state-space equations, has opened up new options and ideas for

analyzing the energy efficiency of various building materials. This method demonstrated that the mass of a building's exterior has a considerable impact on thermal dynamics in long-term energy analysis. However, there were still concerns about using a single-node envelope model for thermally large structures.

To improve the model's performance on high thermal mass buildings, a new second-order model is explicitly applied for modeling the thermal dynamics through the building envelope in [61]. By reducing the square root of the sum-squared-error (SSE) between the step responses of a reference 20th-order model and the 3R2C model, the model parameters are determined. For parametric identification, Kuhn–Tucker equations are utilized to drive multi-variable nonlinear constrained optimization. The performance of the model is compared to that of a 20th-order benchmark model and a first-order based building model. The optimized second-order model's results show a significant improvement in modeling performance over previously proposed, simplified, first-order models. The 3R2C model was just 11% (0.211 s) more expensive to compute than the first-order model (0.19 s) in [66]. However, their work was limited in various ways, the most significant of which was the fact that the parameters were identified based on a unit step excitation.

Fraisse et al. [67] proposed a higher-order 3R4C model to represent the conductive heat transfer dynamics in building envelopes. The concept of aggregating numerous walls in a building into a single thermal network is also proposed; this approach greatly reduces computing costs. When compared to the 3R2C and 1R2C model dynamics, the higher-order model performed better at higher input frequencies. Both 3R2C and 3R4C models have approximately equivalent accuracy at lower input frequencies. The main advantage of the latter is that it reduces the number of calculations as well as the number of parameters that must be defined by the user.

Table 3 presents a few examples of building envelope model configurations that are proposed in the literature. The most used and studied configuration in literature is second-order model (3R2C). However, these models' performance greatly depend on the resistor and capacitor values. Many researchers have solved these parametric identification problems using various approaches to achieve optimal parameter values for efficient model performance. Underwood [74] attempted to address the limitations of [61] by proposing an improved method for adjusting the parameters of the second-order model proposed, which was based on a multiple-objective function-search algorithm that compared the model's response to that of a rigorous reference model. The study also incorporates parametric identification based on periodic excitation, which was another limitation of the previous work [61], which only utilized step excitation. After analysis, the value of the thermal parameters of numerous typical construction elements was included. Boodi et al. [27], on the other hand, proposed an alternative reference model based on unconditionally stable Crank–Nicolson finite-difference models and applied both step and periodic functions to excite the reference and 3R2C models. The difference in both responses may be seen in the high thermal-mass walls result. The reference model's exact dynamics are copied in the model that has parameters that are optimized based on the step response. The same model using periodic input parameters, on the other hand, has a little lower accuracy. It implies that modeling using periodic input is more realistic and applicable to real building dynamics.

There have been numerous studies like this presented in the literature. For parametric identification, there is no defined or standard procedure. Therefore, Section 3 presents a comprehensive analysis of these parametric identifications, optimization techniques, and reference models.

Table 3. Thermal network configurations for building construction elements.

Ref.	External Wall	Internal Partitions	Ceiling	Floor	Windows
[66]	2R1C	1R1C			1R
[70]	2R1C				
[75]	2R1C				
[71]	2R1C	2R1C			1R
[76]	1R		1R	1C	
[72]	3R2C				
[77]	2R1C	1R1C	1R1C	1R1C	1R
[78]	2R1C	1R1C		1R1C	1R
[73]	2R1C	2R1C	2R1C	2R1C	1R
[61]	3R2C	3R2C	3R2C	3R2C	
[67]	3R4C	3R4C	3R3C	3R3C	1R
[79]	1R1C		1R1C		
[68]	3R2C		3R2C		
[74]	3R2C				
[80]	3R2C				
[27]	3R2C	3R2C	3R2C	3R2C	1R
[81]	4R3C		1R	4R2C	1R

2.2. Models for Space-Zones and Their Thermal Interactions with Envelopes

The building model is a composition of the zone envelope model and an internal mass model. The modeling of zone envelopes is relatively simple because of their easily available thermal property or measurement data, and the extensive research done on this topic in literature. Contrarily, internal mass is difficult to model due to the unavailability of the property and measurement data. The internal mass includes internal structures, furniture, carpet, electrical appliances, partitions etc.

The majority of studies have used a capacitor to represent internal mass. The temperature at this point is referred to as the temperature of the indoor air. Liao and Dexter [82] presented a technique for developing a simplified second order physical model to simulate the dynamic behavior of a multi-zone heating system in a residential building. Total resistance and capacitance of the building envelope, and internal mass all contribute to the parameters of a simplified second-order model in their method.

Wang and Xu [83] developed a technique for simulating internal masses. An internal mass was represented using the 2R2C model structure. Floors, partitions, internal walls, and furniture are all constituents of the building's internal mass. These elements absorb radiant heat from windows and inhabitants, as well as from lighting, electrical machines, and other sources, and then gradually releases the heat to the indoor airspace. Furthermore, the parameters of the 2R2C model are determined by reducing the root-mean-square-error (RMSE) between the reference and 2R2C model dynamics using genetic algorithms. When compared to the actual measured data, the performance of the building model with optimal parametric parameters is observed to have an average error of 10%.

Ji et al. [69] proposed an improved approach to the work of [68,83]. The authors reasoned that the previously proposed 2R2C model is insufficiently accurate to account for all internal elements' influences on the cooling/heating load. The results of three distinct models with thermal networks in series and parallel configurations are compared to the results of the reference model. When compared to the measured cooling load, the model accuracy is found to be more sensitive to the distribution of solar radiation than to the classification of thermal mass.

Similarly, Park et al. [84,85] proposed a method for representing electrical appliances in the form of a thermal network. The heat emitted by electrical equipment can increase the cooling demand in a well-insulated building. The authors proposed a 1R1C thermal-network model to study the heat gain from these appliances. Furthermore, considerable research is still needed on internal mass modeling that takes into account all of the contributing factors to the heating and cooling load of internal mass.

2.3. Models for a Complete-Zone Full-Scale Model

A "zone" is an area in a thermal-network model that is developed by assuming a uniform air temperature in an enclosed space. If the internal temperature in all spaces is almost uniform, a full building can be considered a zone. However, in advanced highly insulated buildings, the temperature of each space is maintained differently depending on the needs, therefore a room in a building can be considered as a zone, and zones are interconnected to establish a multi-zone model to represent the entire building. The thermal dynamics of an enclosed space are represented using a zone model. The zone model (full-scale) is composed of 2 models: an envelope model and an internal mass model. The envelope model's outputs are used as inputs in the internal mass model. The thermal network structure of the entire zone model is governed by the envelope and internal mass structures. Some major examples of both full-scale models and reduced-order models are shown in Figure 7.

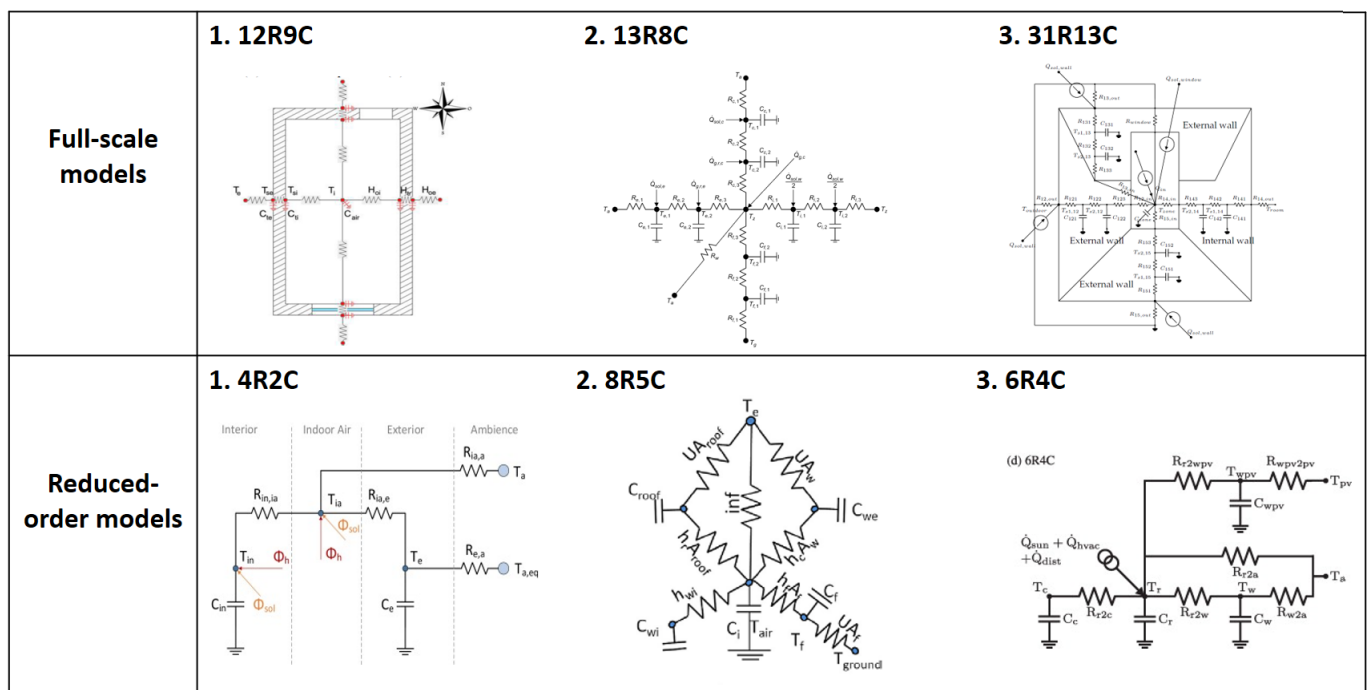


Figure 7. Few examples of full-scale models and reduced-order models Reproduced from: Boodi et al. [27], Braun and Chaturvedi [38], Harb et al. [86], Danza et al. [87], Reynders et al. [88], and Fux et al. [89].

Lombard and Matthews [75] developed a thermal-network model for a zone to integrate the effect of dynamic ventilation. The thermal dynamics of a zone are represented using the thermal network structure of configuration 3R1C. The model is simple, efficient, and accurate enough to reproduce the major dynamics. Despite this, the dwelling's total thermal mass is grouped into a single capacity. Furthermore, there is no differentiation between the fast dynamics of indoor air and the slow dynamics of structural mass. Therefore, higher order models can be used to improve the efficiency of the zone model.

Fraisse et al. [67] developed a zone model that comprises the 3R4C envelope model and the internal thermal mass model, both of which were developed separately. They found that a 3R2C model for an envelope produces results that are as accurate as a 3R4C model. Aside from that, they developed a model for analyzing the interaction of a building's thermal network with the electric and hydraulic heating floor. The performance of the coupled model was compared to the performance of the reference model, and the findings were concluded to be sufficiently accurate. They did not, however, provide a comprehensive explanation of the parameters identified and their physical interpretation. Furthermore,

model for the HVAC system and the interaction between these systems and building zone is studied by Tashtouh et al. [79]. They also included the dynamics of the humidity model in the thermal network and compared the transient responses of the controller and uncontrolled systems. They concluded that the controller is effective in rejecting small error disturbances with a small-time period.

Bacher and Madsen [90] conducted a study on suitable model identification in an attempt to understand the importance of each thermal network element and to determine the appropriate building model to represent heat dynamics. They compared the results of several thermal network configurations, starting with the 2nd-order model and increasing its complexity until a model that included all heat dynamic elements and thermal mass nodes of the zone (5th-order). They compared the performance of ten models using fitting and likelihood ratio tests. The building model was excited by a pseudo-random binary sequence signal (PRBS), which has white noise properties and no correlation with the other inputs. This signal is applied to the heating system and facilitates the creation of suitable models representing the heat dynamics of buildings. The CTSM tool (Continuous-Time Stochastic Modeling) proposed by [91], was used to analyze the obtained time series. It allowed to find grey-box models and embedded parameters (thermal resistances and capacities, for example) using multivariate time series data. The study concludes that model complexity greater than third-order has little influence on model performance improvement.

Palomo et al. [92] used simplified models (2- to 6-order models) to represent a multi-zone individual building. The authors conclude that a second order model can accurately predict daily energy consumption for the tested individual building, but a fourth order model is recommended for high-quality indoor air temperature and heating load power prediction. Meiri et al. [93] developed and compared gray box models with orders ranging from 1 to 5 and observed that increasing the model order beyond 2 does not result in a substantial performance improvement and may even lead to inaccurate results.

On the basis of indoor temperature prediction, models with orders ranging from one to four are compared [89]. The model's states and parameters are estimated using an extended Kalman filter (EKF). The results show that the 1R1C model is adequate for reproducing the thermal behavior of a passive building. The model is also tested for two-day and four-day predictions, the author concluded these models could be useful in short-term controller applications. A study on model identification was also conducted by Massano et al. [94]. The EnergyPlus model is used as a reference for comparing the results of the first and second-order models. The performance of the first-order model with coupled parameters resulted in the MAE and RMSE below 0.37 °C as compared to second-order models with MAE and RMSE above 0.7 °C. This indicates the first-order model outperformed other models with both coupled and separately identified parameters. Because the parameters of the thermal-network model are interconnected, they must be estimated as a whole rather than separately. All of these models, however, are calibrated and validated using sensor data from the identified building during an unoccupied period. Whereas, Berthou et al. [95] developed four different thermal-network models of orders two and three. In each model order, the number of resistors and the position of thermal mass nodes are changed. Using real dynamic occupancy data, the models' indoor temperature and heating load predictions were evaluated. The performance of the models is compared for both heating and cooling period predictions, the 6R2C model performed better than other models by resulting in below 2% error from the best result.

The approaches for developing thermal-network models are detailed in the guidelines VDI 6007 [96] and DIN EN ISO 13790 [97]; the former presents a second-order model for simulating a zone, whereas the latter presents a first-order (5R1C) model for zone temperature and heating load prediction. However, the 5R1C model cannot be implemented when the ventilation or infiltration dynamics are included in the model as division by zero may appear when these two airflows are zero. Furthermore, neither of the guidelines discusses any fitting methods or parametric identification based on the measured data. Michalak [98]

presented a modified 4R1C version of the 5R1C model to address the problem of ventilation or infiltration dynamics, in which the existing ventilation heat dynamics was replaced with a new heat flux, which relates to the time-varying airflow caused by infiltration and ventilation. The model is validated against the EN 15625 standard, BESTEST tests, and EnergyPlus data.

Harb et al. [86] presented a similar model identification study and compared the model performance to real data collected from reference building. Because the authors had no prior knowledge of the physical properties of building materials, the parameters were determined inversely using the Interior Point (IP) optimization technique. Multiple norms and guidelines are used to determine the parameters physical probable value range for various physical characteristics [96,99–102]. The developed models were of configurations 1R1C, 3R2C, 4R2C, and 8R3C. These models were evaluated from both a statistical and a physical standpoint. The result conclude that in comparison to the simpler 4R2C model, the complex 8R3C model shows no significant improvement in performance. A similar study was carried out in [103], the authors developed 1st, 2nd, and 3rd-order models to predict real-world building thermal dynamics. The inverse technique and the system identification algorithm are used in MATLAB [104] to identify model parameters. The residual auto-correlation study shows that the second order model accurately represents the building thermal dynamics, but it also reveals that the model cannot account for certain behaviors and approximations. User bad-behaviors, measured signal aliasing, and a low correlation between the measured temperature and the temperatures of the represented thermal zones can make identification difficult, and even give a poor result in terms of accuracy.

The application of lumped parameter models is mainly used for thermal dynamics analysis that is focused on capturing the sensible heat dynamics. However, this approach has been also tested and validated for hygric models. Kramer et al. [105] proposed a methodology to develop both thermal and hygric models, they developed 10 thermal and 5 hygric models for comparative analysis. Both the models are identical in structure, with vapor pressure serving as the driving force and solar irradiance being excluded as an input in the hygric model. The performance of these models is compared with measured data from four monumental buildings using a residual and parameter analysis. The results suggest that for long-term simulations, the simplified hygrothermal model is capable of accurately simulating most indoor climates (1 year).

Nevertheless, numerous studies have been undertaken on the development of zone models utilizing the whole model dynamics by representing each element in order to capture all thermal dynamics associated with the zone. Models with numerous thermal components have a higher level of performance accuracy than models with a small number of thermal elements. Sayadi et al. [106] proposed a building model with a 9th-order thermal network that contains a thermal network for each construction element (external walls, internal walls, roof, and floor). The model is trained and validated using the measured data from the building. An MPC model is implemented based on the full-scale zone model, the results show that whole zone model performance is accurate enough for MPC and they achieved 43% and 31% reduction in the overall energy use during the estimation and validation periods, respectively. However, the envelope in this study is represented using a 2R1C thermal network, which may not be appropriate for heavy thermal mass walls. As a result, ref. [27,65] proposed a full-scale model that contains a 2nd-order thermal network representation of each envelope element. The results show that the model's accuracy is acceptable in both summer and winter simulations. The winter results, however, have a MAPE (Mean Absolute Percentage Error) of 6.53% and an RMSE of 0.69 °C, which is higher than the summer MAPE of 4.71% and RMSE of 0.61 °C. This is due to unaccounted heat gains from the occupants during winter.

The higher order full-scale models are capable of capturing the majority of the building's heat transport dynamics and accurately estimating indoor temperature and heating/cooling demand. When modeled for multiple zones of a building, however, the

computational cost and complexity of these full-scale models increases. A 4-zone building model, for example, may have a state-space dimension of 40 or more, whereas a 100-zone building could have a state-space dimension of a thousand. Thus, such a model is unsuitable for a model-based control technique, particularly one requiring on-line optimization based on model prediction, such as MPC. Therefore, for reactive building energy management systems, reduced-order models are necessary [107]. Goyal and Barooah [108] proposed a model reduction methodology based on a balanced truncation method for LTI systems and balanced truncation-like reduction method for nonlinear thermal building thermal models. The measured RMS error in temperature predictions over a 24-h period is 0.5 °C when the model is reduced from 40 to 14 states. When the same model is reduced to 8 states, the observed RMS is 2 °C. Therefore, for modeling multi-zone buildings, such methods are essential. The computational cost comparison between the full-scale model and reduced-order models is shown in Table 4.

Table 4. Computation time vs. model order. Reproduced from Goyal and Barooah [108].

Model	Model Order	Computational Time
Full-scale	40	189–397 s
Reduced	14	38–77 s
Maximally reduced	8	32–64 s

Table 5 summarizes the critical analysis of the contributions and main limitations of full-scale models that are developed for both single-zone and multi-zone buildings. In this context, the significance of model parameters, sensitivity analyses, generic thermal models, accurate internal thermal mass models, and the effects of residual analysis, simulation-times, -steps and -periods are not addressed clearly. These potential areas should be assessed in detail to achieve efficient, simplified, and low computational cost building thermal-network models.

Table 5. Analysis of whole-zone models based on the thermal network approach.

Reference	Building Type	Zone Structure	Single-Zone	Multi-Zone	Contributions	Limitations
[109]	Micro-homes	3R1C	✓		Passive heating is proposed for heating/cooling load reduction	Effects of all thermal dynamics are not taken into account
[110]	Office	4R4C	✓		Hybrid building modeling method with a reduced modeling and calibration effort	The use of two different modeling techniques requiring different sets of skills from the modeler may be an obstacle for its practical implementation
[111]	Office	3R3C	✓		The definition of the differential equations that govern the system is unnecessary, and less inputs and a priori information are required	GP presents a higher day-ahead prediction error, it requires longer training periods and is more sensitive to unknown input data
[108]	-	40 states		✓	The non-linear higher order model is reduced using balanced truncation-like model reduction method	Effect of all thermal dynamics are not taken into account
[81]	Residential	31R6C	✓		Lumped-capacitance building model with an HP based heating system managed by a predictive control, that allows some degree of flexibility to space conditioning	Node positioning is not discussed
[112]	Single-room	4R3C	✓		A novel optimization method is proposed for parametric identification	There is little difference between the results of PSO and BSAS, and the stability of the proposed algorithm should be studied for higher-order RC networks

Table 5. Cont.

Reference	Building Type	Zone Structure	Single-Zone	Multi-Zone	Contributions	Limitations
[87]	-	12R9C	✓		3R2C envelope model is used to constitute whole-zone model	Sensitivity analysis is not discussed. The parametric identification method and node positioning is not discussed
[113]	Demonstrator building	11 states	✓		An MPC is applied to control the indoor space based on the comfort index PMV	Positing of nodes is not discussed
[98]		4R1C	✓		The model performance accuracy is better than EN ISO 13790 model	Positing of nodes is not discussed. Sensitivity analysis is not discussed
[114]	Industrial building	55 states		✓	This algorithm defines basic structures in model as sources, spaces, walls and openings, and enables rapid and automated development of thermodynamic model of a building in state-space representation, based on basic information about the building	Calculation of RC values in white box model is not clear. The author states that the values correspond to layer values but wall composition is not presented in the paper. The results are shown for 1 day and these are not properly fit with the measured data
[115]	Single-room	5R1C, 7R2C	✓		Both lumped-capacitance models appear to reliably calculate the overall energy needs of buildings in both heating and cooling seasons. As far as transient behavior is concerned, the first-order ISO 13790 model seems inappropriate to calculate neither the hourly cooling load profile nor the cooling peak load. The second-order model proposed by VDI 6007 is more accurate in both the heating and cooling modes	The current study hopes to be useful to building designers who must choose between simplified simulation tools based on the standards mentioned and to researchers who intend to integrate the lumped-capacitance models presented here into city district simulation tools
[116]	Test room		✓	✓	The two-node model for one room presented in this paper gives reasonably good results for a variety of typical wall constructions. The extension of the model for a multi-zone building on the base of the two-node model seems to reproduce with good accuracy the results obtained by the dynamic thermal simulation program ESP-r	Of these, the explicit solution methods are too onerous for general purposes, both computationally and in terms of data requirements (and associated uncertainties)
[117]	Office		✓		It has been proved that the analytical solution is asymptotically stable for all time steps, and therefore, there are no constraints on the feasible search region of the RC parameters	This model is proposed as a simplified but robust model, which is embedded in existing and future BAS without the need to install additional sensors
[118]	Historical building			✓	The study found that combining a high thermal-inertia-mass with a ventilation system eliminates overheating and improves indoor comfort while lowering cooling loads.	The model should be tested and validated for other types of buildings.

3. Parametric Identification

Gray-box models are a hybrid of white-box and black-box concepts. The system's equations are obtained using physics, thermodynamics, and heat transfer theories. The lumped-parameter model is used for buildings, and is capable of capturing all the zone's heat dynamics [119]. The challenge arises, however, while defining the lumped model's parameter values [120]. When operational data (measured sensor data) is unavailable and only thermo-physical characteristics are available, the parameters can be determined analytically [121,122], or by developing an analytical model as a reference model using available data and matching the resultant dynamics of the thermal network and reference models [74,80]. However, if there is good availability of measured data but a lack of thermo-physical characteristics data, inverse methodologies [123–125] are applied to determine parameter values by minimizing the prediction error between the thermal-network model and the measured data [126–129]. We may categorize parametric identification methods into three groups based on the numerous methods provided in the literature:

- Forward/direct methods
- Inverse methods
- Hybrid methods

3.1. Forward/Direct Methods

The direct/forward methods are developed based on analytical models. The parameter values of the thermal-network model are derived analytically. In general, the analytical models need complete data for geometry, thermo-physical properties of the construction materials, etc. Analytical parameter identification methods can be complex, and their accuracy can be questioned in some cases, whereas optimization-algorithm-based methods are more accurate, however, require prior simulation using a detailed or high-order reference model, and thus, are not suitable for use in buildings or urban micro-climate thermal simulation programs (as the characteristic parameters of the model must be adjusted beforehand for each element). Thus, it is necessary to find an analytical adjustment method (that does not require prior simulation using a reference model) that offers sufficient accuracy, maintains simplicity (therefore a low computational cost) and can be adapted to changes in the value of the simulation's time step.

Ramallo-González [120] proposed a new approach based on the Dominant Layer Model (DLM) as an alternative to analytical methods for developing thermal networks for multi-layered composite walls. The authors investigated the relative influence of each layer in a frequency-response multi-layer wall. This method includes a set of rules to define thermal network parameter values. The model's overall accuracy outperformed Fraisse's model [67] in both the time and frequency domains when results were compared.

Furthermore, Rodríguez Jara et al. [130] introduced an analytical approach for determining the parameter values based on a hypothesis that these values are time-dependent and vary throughout the simulation. They validated the proposed approach on 41 different types of multi-layer walls by comparing it to the reference finite-difference model. However, there is a lack of detailed analysis on full-scale model simulation using the developed approach.

Analytically determined parameters can result in more efficient model development. However, in order to develop such models, the researcher must have strong analytical knowledge, and sometimes the design process can become complex and time consuming, leading to the results diverging from the expected results for multi-zone models. Furthermore, these methods can only be implemented if all possible thermo-physical knowledge of the building is available. Therefore, researchers have proposed an inverse method to overcome these drawbacks.

3.2. Inverse Models

Inverse modeling is the process of taking measured sensor data from the building as an input to determine the parameters or perform system identification. These methods determine parameters by minimizing the error between the measured and simulation results. Two types of inverse problems are [131]:

- Parameter estimation: Inverse modeling is used to determine the parameters, such as resistor or capacitor values in the thermal-network model. These parameters will have some physical meaning and boundaries during the optimization.
- System identification: The inverse modeling is applied to identify complete systems with all parameters that may or may not have any physical meaning. These models use patterns to predict the system's dynamics.

The general optimization process is shown in Figure 8, the building model is represented in state-space models with state and parameter values. The simulations that do not need to be repeated are performed at the initialization stage. Parameters of the state-space equations are initialized for the first step of the simulation; the response is compared with the measured/reference model data. Furthermore, optimization techniques are applied to find the optimal parameter values that produce global minimum error values. This new

set of parameters is then used for the prediction of indoor temperature or heating/cooling load.

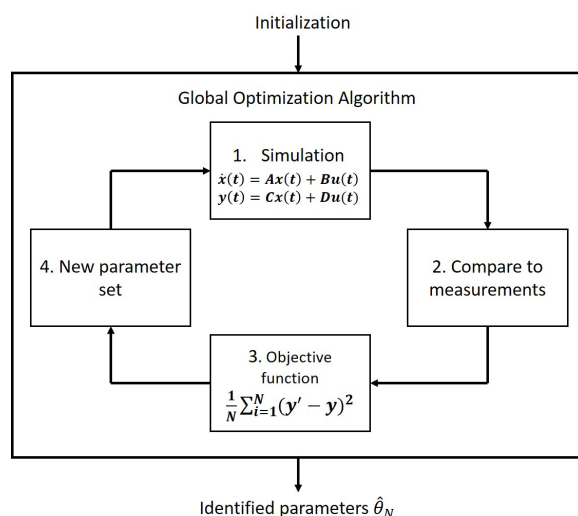


Figure 8. Optimization process. Reproduced from Kramer et al. [105].

Early implementation of parameter identification was proposed in [132] where the RC model of structure 3R2C is developed for a school building. The resistor and capacitor values are determined using the least squares optimization algorithm. The identified parameters were, however, showing average differences of 25–30% compared to real values. Furthermore, they found that the methodology is computationally expensive and not suitable for integration with BEMS. Later, they proposed an improved recursive least squares method in [133] to integrate the thermal-network model into BEMS for on-line control applications. This study opens up the possibilities of developing thermal-network models for retrofitted/new buildings, and controller applications, that do not require knowledge of the thermo-physical characteristics of the building.

Madsen and Holst [76] worked on the estimation of continuous dynamic models from discrete measured data. The parameters in continuous-time models are estimated by the maximum likelihood method where a Kalman filter is used in calculating the likelihood function. The authors concluded that more reasonable physical interpretations of parameters are possible for continuous-time parameter estimation. Another study [134] applied the same methodology to identify the parameters of a higher order thermal network-model. They added white noise to the measured data to compensate for any error in the measurement. The model includes adjacent room air temperature, power from radiators and EC-units, and outside air temperature and solar radiation for the south and north side, respectively. The results show that the model was able to simulate the system with a maximum difference between the simulated and measured temperatures of 0.40 °C during the simulation period of 17 days. Furthermore, a methodology was proposed in [135] to find a model linking the heat consumption to climate and calendar information by using statistical algorithms to identify the parameters.

Mustafaraj et al. [136] conducted a comparative study on different stochastic algorithms such as Box–Jenkins (BJ) models, autoregressive models with external inputs (ARX), autoregressive moving average models with external inputs (ARMAX), and output error (OE) models to identify the thermal behavior of an office positioned in a modern commercial building. The models were trained and validated throughout the weekdays of the summer, autumn, and winter seasons, to study the thermal behavior of the zone, and two major influencing output parameters (temperature and relative humidity) were chosen for prediction. The results show that the BJ model provides better prediction results than ARX and ARMAX models (see Tables 1–6 in [136]). The out-performance of BJ models being due to its handling of noise being more suitable than other algorithms. Furthermore, these

algorithms are adaptive to the changing conditions of the building systems. In this regard, such algorithms are better suited for on-line controller applications in buildings [137]. Similarly, Unscented Kalman Filtering (UKF) is implemented for on-line thermal parameter estimation for multi-zone buildings [138], and Sequential Monte Carlo methods for 3R2C models [139].

Lin et al. [140] presented a study on the identification of a suitable reduced-order model to represent the actual building dynamics and the estimation of its parameters. The authors compared the performance of full-scale (13-order), first, and second-order models with the measured data. Here the parameter values for the full-scale model are taken from ASHRAE standards, [15] and for reduced-order models, the same values are aggregated to represent the parameters. Three different (open and closed-loop) measured data sets are used for model performance comparisons in both the time and frequency domain. The results show that the second-order models are accurate enough to capture the influencing dynamics of the building. Furthermore, least squares and maximum likelihood optimization techniques are compared for parameter estimation. As the cost functions are non-convex, gradient based optimization techniques often fail to find the global minimum, this is a normal condition of higher number parameter models. Therefore, the direct search method is used for minimizing the cost-functions to avoid getting stuck at the local minimum. The least squares method is found to be more accurate in closed-loop data cases, whereas ML is better for forced-response data.

Many studies have used a readily available system identification toolbox of MATLAB for the parameter estimation process [141,142]. Afshari and Liu [143] presented a study on the urban energy model to estimate the urban heat intensity (UHI) and UHI cooling load penalty. A third-order thermal network urban energy model is developed and the parameters are identified by calibrating the model with measured hourly data. The best parameter estimation results are obtained using genetic algorithms and particle swarm optimization techniques (PSO) and the former was retained for model simulation. However, stochastic optimization algorithms are time-consuming due to the large number of populations being randomly initialized to accomplish optimization.

Whereas Wang et al. [112] proposed a novel optimization algorithm known as beetle swarm antenna search (BSAS) for the estimation of parameters in building thermal-network models that has a low computational cost and an acceptable accuracy. Seven total R and C values are estimated by minimizing the mean absolute difference between the thermal model and EnergyPlus-predicted indoor temperatures. The BSAS algorithm's performance is compared with other algorithms such as GA, PSO, and DE. The results show that BSAS with beetle number 5 shows better stability with high computational cost, whereas beetle number 2 produces a slightly higher error with a low computational cost. However, PSO results were more stable than the BSAS with beetle number 5. However, the proposed optimization algorithm needs to be tested on higher-order thermal-network models.

Due to an increase in the implementation of IoT devices in buildings, the availability of large datasets has led to an increased use of inverse-algorithm based building-dynamic-model development. As a result of the modeling simplicity and availability of powerful computational machines, these algorithms are used for model identification, parametric identification, model order reduction, and estimation of thermal characteristics of the buildings. Furthermore, the fusion of multiple inverse algorithms has been shown to lead to the development of robust models with excellent indoor environment parameters, and heating/cooling load prediction accuracies [134,144]. As seen in Table 6, many different inverse algorithms are used in the literature. These algorithms are broadly classified into three categories [131]:

- Deterministic models
- Stochastic time series models
- Black-box models

However, the accuracy of this type of inversely developed model heavily depends on the accuracy of collected data. Most of the time data collected are prone to have measure-

ment errors, and such data leads to models with estimated parameters that produce large errors [145]. Some of the inverse models are critically reviewed with different parameters in Table 6. Many studies have been applied to whole-zone model parameter estimation, and they show greater accuracy when compared with the measured data. However, a lot of work is still required to focus on the uncertainty analysis of the measured data [146], model validation through long-term simulation, dynamic occupancies, physical interpretation of estimated parameters, sensitivity analyses, training and testing periods, and input variables.

Table 6. Analysis of inverse model developed on optimization algorithms.

Reference	Building Type	Thermal-Network Model	Optimization Method/Algorithm	Simulation Tool	Simulation Period	Performance Metrics	Contributions	Limitations
[60]	University	Multi-zone	Maximum likelihood estimator	MATLAB	48 h	Sum squared error (SSE)	Convective heat transfer between zones is considered and parameters are estimated for the same zone	Zone temperatures are maintained at a constant value (closed-loop data), this is likely to lead to grossly inaccurate parameter estimation
[147]	Residential	5R2C	Least squares identification	MATLAB	120 days	fit	The models for input systems are modeled and linearised to obtain simple models	Physical interpretation of obtained parameter values are not studied. Furthermore, the boundaries of parameter values are not clearly stated.
[105]	Monumental	Multiple configurations	GA, pattern search, fmincon	MATLAB	1 year	fit, mean squared error (MSE), mean absolute error (MAE)	Simplified hygrothermal model is developed with multiple parametric optimization methods. Indoor temperature and RH are predicted for free floating monumental building with higher accuracy	Sensitivity analysis is not conducted. The computation time complexity for optimization process is high, as is the difference between each optimization algorithm output parameter.
[95]	Office	6R2C	Interior point algorithm		Training : 1,2,3 weeks, Test : 3 weeks	fit, RMSE, energy relative error (ERE)	Multiple RC models are compared. Sensitivity analyses of parameters are presented.	Robustness of the proposed model should be validated for long-term predictions.
[89]	Lodging	1R1C	Nelder–Mead simplex algorithm		Parametric estimation : 12 days, model simulation : 2 and 4 days	RMS and MAE	Multiple RC models are compared. On-line estimation of occupancy heat gains is estimated and included in the model.	The model should be validated for long-term predictions. Physical interpretations of parameters are not included.
[123]	Residential	Envelope model - 2R1C	Bayesian analysis	CERN MINUIT [148]	14 days		Combining physical and Bayesian analyses lead to significantly reduced measurement periods required to estimate U- and R-values compared to conventional steady-state methods.	Lower order RC model is not suitable for the high thermal mass walls. Robustness of the methodology should be verified for different materials.
[111]	Office	3R3C	least squares algorithm	MATLAB	3, 7, 21, and 42 days	RMSE	Gaussian process (GP) is developed to represent building dynamics. The prediction errors for occupied period are 27% lower than gray-box models.	Long-term simulation is not studied. Dynamic occupancy, and other heat inputs are not fully taken into account.

Table 6. Cont.

Reference	Building Type	Thermal-Network Model	Optimization Method/Algorithm	Simulation Tool	Simulation Period	Performance Metrics	Contributions	Limitations
[149]	Office	Envelope model - 2R1C and 3R2C	Maximum a posteriori (MAP) and bayesian analysis	SciPy [150]	3 days	fit	R and C values are estimated for building envelopes based on in-situ measurements. The positioning of R and C parameters are optimally positioned in 3R2C model	The methodology to chose parameter boundary values is not clearly presented.
[142]	Office	4R2C	System identification toolbox	MATLAB	1 day	fit	EMs are developed based on mixed integer linear programming (MILP) to optimize the bi-directional energy flow while managing thermal comfort.	Selection of model structure is not discussed. Physical interpretation of each parameter is ignored.
[151]	Office	Multi-zone	GA and Prediction Error Method (PEM)	MATLAB	17 days	fit and RMSE	Model reduction by removing non-identifiable parameters is presented. This also reduced the model uncertainty significantly.	Zone temperatures are maintained at a constant value (closed-loop data), this likely to lead to grossly inaccurate parameter estimation
[152]	University	3R2C	Profile likelihood method [153, 154]			RMSE	UKF and EnKF have been compared for the purpose of estimating residuals and covariance for evaluation of the likelihood function.	Closed-loop data is used for validation, this is likely to lead to grossly inaccurate parameter estimations

3.3. Hybrid Models

These models are the combination of the direct and inverse method. Direct methods are computationally inefficient and complex to model, whereas inverse models are simple and computationally efficient but need a large amount of data in order to train the model or identify the system parameters. In all new or retrofitted buildings, where there is lack of availability of building operational data, the application of inverse models becomes impractical. Furthermore, to avoid poorly estimated models from noisy measurements with high uncertainties, many studies have been undertaken on developing reference models based on analytical or numerical methods. Hence, using optimization techniques for parametric identification of thermal-network models reduces the error between the reference and thermal network-models.

Antonopoulos and Koronaki [155] proposed a hybrid method that developed a reference model based on the finite-difference method. The apparent thermal capacitance of a building is determined using the least squares optimization technique. These thermal capacitance values have a significant influence on thermal model performance accuracy. They validated their approach on various buildings in Greece.

Gouda et al. [61] applied a constrained optimization technique to identify the parameters of the thermal-network model by minimizing the error between reference model dynamics. They developed a 20th-order thermal-thermal-network modelnetwork model to replicate the envelope dynamics, and also used it as a reference model. Similarly, Fraisse et al. [67] developed a frequency response model as a reference model. Underwood [74] developed a numerical method based on an implicit finite-difference model as a reference model. Similarly, Harish and Kumar [80] used the finite-difference Crank–Nicolson numerical model as a reference model for 3R2C envelope model parameter identification. The model parameters are determined for step responses in outdoor temperature and relative humidity. Xu and Wang [64,156] compared the Conduction Transfer Function (CTF) model

with the 3R2C model for parameter estimation. They validated the building model with measured data. These identified thermal models are later used to develop a full-scale zone model for validation with measured data [27]. Apart from analytical and numerical models, software tools (EnergyPlus, TRNSYS, and ESP-r) are also used as reference models for system and parameter identification, and validation.

Models that have been developed based on hybrid modeling lead to high performances and accuracies with a loss of modeling complexity. Furthermore, reduced-order system identification based on a reference model for multi-zone models can lead to high computational costs and complexities. Whereas, full-scale models based on envelope and internal mass models reduce the complexity for a single-zone model. However, these become complex for multi-zone models. Therefore, there is still more research needed on hybrid modeling and model-reduction methods.

4. Conclusions and Perspectives

More and more use of sensors, connecting devices, and advanced technologies have enabled efficient building management and control. These controllers' performance is predominantly dependent on the building models that can replicate real building dynamics. In addition, during the design and planning stage of building constructions, such simplified models will be important in selecting the suitable materials, orientation, operation schedules, and systems combination. Thermal network method-based building models have the ability to predict and replicate the building dynamics with a high accuracy. Other advantages are its low computational cost (models based on state-space representations), robustness, reduced-order modeling, simplicity to develop, development even with limited/no thermo-physical properties data, and suitability to controller applications.

Recent studies have shown that MPC controllers based on thermal-network models are able to better manage occupant comfort while achieving significant energy consumption reduction. However, these models become complex for multi-zone buildings without proper model reduction techniques. Additionally, the system's parameters have significant influence of the model performance, therefore proper parameters' estimation is required. More study is needed in this area since physical knowledge of thermal network parameters, node placement, and sensitivity lacks adequate explanation and interpretation. Furthermore, there is a lack of explanation on network structure selection for envelope model, internal mass, and zone models. Further research is required on this aspect to develop a generic model that is adaptable to all conditions and building types.

A critical and extensive review is carried out in this study to addresses thermal network method-based modeling types, applicability, advantages, model-reduction methods, reference models, and parameters identification to achieve a high-performance model to predict building dynamics. These thermal network method-based models are reviewed in detail for building envelopes, internal thermal mass, and zone models. We have also reviewed different methods for parameter identification. More research has been done on the inverse gray-box models with parameters are estimated by calibrating model with measured data. However there is a lack of detailed explanation of the parameters' physical interpretations. Furthermore, in the literature, thermal-network models are predominantly applied for buildings by only considering the sensible heat transfer dynamics and the latent heat being completely ignored. They also have a significant influence on the indoor conditions and heating/cooling load predictions.

In this regard, significant research is still required on many themes of the thermal-network models for building modeling, some of the most important and potential areas are listed below:

- The models that are developed for envelopes are not generic and multiple configurations are presented. Therefore, research on development of a generic model to represent thermal dynamics through building envelopes (considering multiple types of thermal mass walls) is essential.

- As noted by authors, full-scale models are accurate but become complex when applied for multi-zone buildings. More research is needed on model reduction and calibrations techniques.
- In most studies, there is still a lack of analysis on the models' suitability for seasonal variations, dynamic occupancy, and short and long-term simulations.
- Analysis of proper input selection and consideration of all influential inputs is still required.
- Comprehensive analysis on the development of hygric models (including latent heat and mass transfer dynamics) is essential. These models can be used to simulate indoor thermal conditions with greater accuracy.
- Most parametric and system identification studies lack a thorough explanation of model structure selection, physical interpretation of identified parameters, and boundary values selection during the optimization process.
- Uncertainty analysis of measured and simulated data is still poorly studied in the literature and has not been considered in most studies.

Finally, the prospective areas discussed above must be addressed in detail to design and develop a building model that is accurate in predicting indoor conditions and can be applied to all building types and conditions (generic model). Such models open the way for a significant industrialization of intelligent controllers, inclusion in digital twins, and the incorporation of all other comfort variables, as well as the realization of sustainable building development (in operation stage).

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial neural networks
ARMAX	Auto-regressive moving average with external inputs
ARX	Auto-regressive with external inputs
BEMS	Building energy management system
BIM	Building information modeling
BJ	Box-jenkins
BSAS	Beetle swarm antenna search
Bi	Biot number
CSTM	Continuous time stochastic modeling)
CTF	Conduction transfer function
DLM	Dominant layer model
EKF	Extended Kalman filter
EMS	Energy management systems
ERE	Energy relative error
EU	European union
GA	Genetic algorithms
GHG	Greenhouse gases
GP	Gaussian process
HVAC	Heating, ventilation, and air-conditioning systems
IEA	International energy agency

MAE	Mean absolute error
MAP	Maximum a posteriori
MILP	Mixed integer linear programming
MPC	Model predictive controller
MSE	Mean squared error
NZE	Net zero energy
OE	Output error
PCM	Phase-change materials
PEM	Prediction error method
PRBS	Pseudo-random binary sequence signal
PSO	Particle swarm optimization
RL	Reinforcement learning
RMSE	Root mean square error
SSE	Sum squared-error
SVM	Support vector machine
TRNSYS	Transient system simulation tool
UHI	Urban heat intensity
UKF	unscented Kalman filtering

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